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Procedia Computer Science 22 (2013) 1092 – 1101

Procedia Computer Science

17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems - KES2013

Modified Hybridized Multi-Agent Oriented Approach to Analyze Work-stress Data Providing Feedback in Real Time

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Abstract

This paper presents a hybridized multi-agent oriented approach to develop a model capable of classifying and linguistically grading the level of work-stress. The scope of this research is to implement the model to solve a psychological problem relating to work-stress. The model uses a neural network capability as agent to classify the work-related stress data. The fuzzy logic component then transforms the crisp output from the neural network into linguistic grade. The main idea of integrating neural network and fuzzy logic techniques was to neutralize each other's weaknesses and generate a superior hybrid solution. The work-stress data was analyzed using the model and feedback provided to the users about their stress levels in real time. The result demonstrated that using this technique, the work-stress data was classified efficiently and the measured stress level was successfully described in linguistic term (Human readable). This achievement provides the user with an automated mechanism that can render a first step towards identification, prevention and making perceptible changes to the working environment. The Intelligent Multi-Agent Decision Analyser (IMADA) uses a hybridized technique that provided better solution in terms of applicability, portability and efficiency in this particular psychological domain.

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Keywords: Agents; Artificial Intelligence; Multi-Agent Systems; Fuzzy Logic.

1. Introduction

Problem solving, data analyzing, decision making are complex tasks that require techniques that are feasible, cost-effective and efficient. Neural networks and fuzzy logic techniques have been widely used to develop many applications. The Berkeley Initiative in Soft Computing (BISC) was launched in 1981 to recognize modern software programming techniques used for problem solving. Examples includes; neural networks, fuzzy logic and

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doi:10.1016/j.procs.2013.09.195

genetic algorithms. These techniques are mostly referred to as intelligent techniques because each has its own strengths and weaknesses making it difficult to solve all problems on their own. Thus integrating two or more techniques to solve problem can provide better solutions, with increase precisions, especially with psychological data analyses. Work related stress affects people from all professions in life and has become a widespread concern in Australia and other countries. Work related stress can be prevented if it is assessed in a timely fashion within the organization. Recognition must start at the workplace by the employer or the organization, where management can signal awareness that stress may be a significant occupational health and safety issue [1]. Organizations need to assess workplace related risk factors stress and for that a tool is needed using which they can make the first move to assess and prevent work-stress. Thus there is a need for a reliable psychological risk assessment system that be used by individual user or users from organizations. In order to assess such psychological risk arising with the workplace, an autonomous intelligent agent based model is developed [2]. The model uses the Intelligent Multi-Agent Decision Analyser (IMADA). This analyzer comprises of four components namely; database agent, neural network agent, knowledge agent and a classifier agent [2–4]. This paper presents a modified model where the classifier agent is replaced with a fuzzy logic agent containing fuzzy logic capabilities. It is then integrated with the neural network classifier. In Section 2 the modified model is discussed, followed by Artificial Neural Network (ANN) and Fuzzy logic in Section 4, finally the results and outcome from the modified model are presented Section 5 with the conclusion and future work in Section 6.

2. Modified Model

The modified model uses a fuzzy logic capability as agent that replaces the classifier that was implemented in the earlier model [2–4]. An brief introduction of agents and multi-agent systems are given in subsection 2.1 followed by the modified hybridized model in 2.3.

2.1. Agent and Multi-Agent Systems

An agent is a software or hardware entity that autonomously reacts to changes in the environment through the use of sensors and actuators [5]. Wooldridge and Jennings [5] state that an agent is a hardware and/or software based computer system which display autonomy, social adeptness, reactivity, and proactive. Agents are most commonly used in challenging or changing, dynamic, unpredictable, and unreliable environments. An Intelligent Agent (IA) can be defined as:

1. Software process that fulfills a stated need or activity on behalf of an user,
2. That uses the knowledge base and build-in to accomplish task user defined task by making decision,
3. Also knowns as bots or software robots.

Franklin and Graesser defined an autonomous agent as “a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future” [6]. With growing tend towards interconnection and distributed architecture. Systems are developed that contains a number of sub-system that must interact and cooperate to reach a solution. The notion of Multi-Agent System (MAS) began to gain prominence in the early 80’s. Newell and Simon developed the production system which was based on the collection of pattern, that worked by forward chaining of the rules [8, 9]. The key issues of the production system was knowledge structure, which in this case was unstructured. The need for structured knowledge led Englemore and Morgan in the year 1988 to work on the *blackboard systems* that was recognized as MAS [10]. The environment in which the agent operate can be computational and physical which can be open or closed. With the increase in interconnection and networking, situation may arise where agent react with others agents. The MAS framework or architecture represents a new way of conceptualizing and implementing distributed software because the MAS framework is composed of multiple interacting computing elements or components [5]. MAS designs are being used pre-programmed to pursue the goals [7] where resources can be shared among one or more agents [11]. This concept have been used to develop the present hybrid model presented in subsection 2.2.

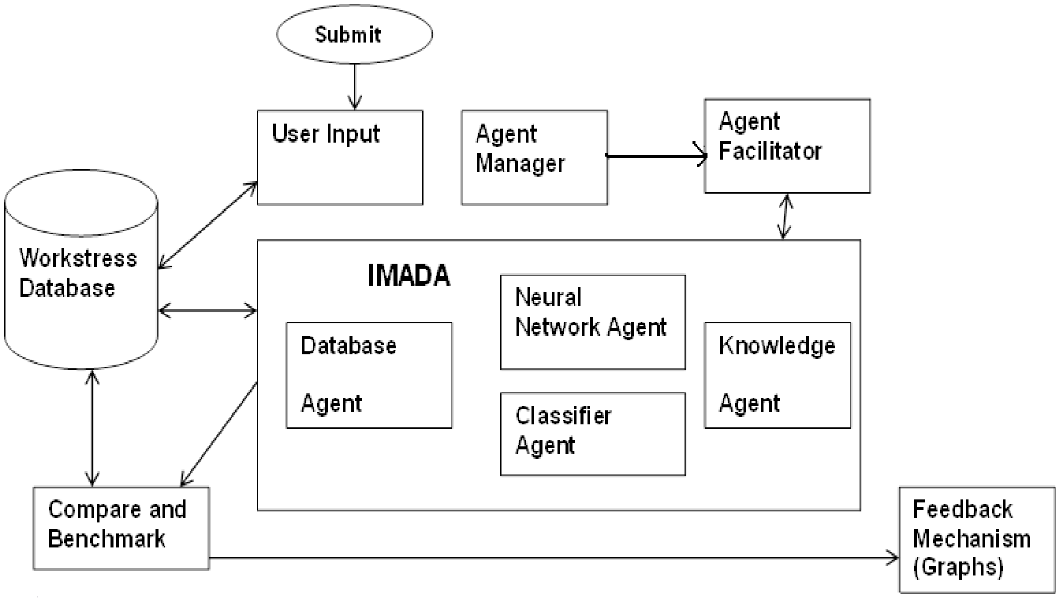

Fig. 1. Framework of the model developed using IMADA

2.2. Present Hybrid Model

Hybrid intelligent systems consist of multiple parts or components that are combined to perform a specific task. Hybrid systems form a part of complex problem solving and decision making process. These systems are not adaptive making it hard to replace a technique if a better one has been found. Agent oriented approach provides better solution as they are flexible, can adept to changes at run-time rather than design time. Thus a MAS platform is suitable for modeling, design, and construction of hybrid intelligent system [12]. The present model uses an analyzer developed using intelligent techniques to process the users work-stress related data. Prior to the development of this autonomous model, the same data was processed manually using Software Packages for Social Sciences (SPSS). To optimize the data analyses process, the framework that has been used to develop the present model Intelligent Agent Framework (IAF) [2–4] was transformed to incorporate MAS linked to create an analyzer. The new designed analyzer was renamed as IMADA shown in Figure 1.

As suggested IMADA contains four components. These are database, neural network classifier, fuzzy logic and knowledge repository. The four components are individually developed and integrated to operate autonomously and accomplish their desired goal. The database management components maintains and updates the user and the national benchmark database. The neural network component uses the back-propagation algorithm and programmed using Java. Fuzzy logic component processes the output from the neural network and transforms into a linguistic grade. The analyzing component has been developed using two hybridized artificial intelligence technique; neural network agent and a classifier agent. The results obtained using the new analyzer, replicate and in some cases show superior results to previously analyzed records [2–4].

2.3. Modified Hybridized Model

The modified model replaces the classifier agent with fuzzy logic capability as agent. The output from the neural network will be processed by the fuzzy logic agent, providing a gradual transformation of the crisp output to a more human readable format using linguistic outputs.

3. Artificial Neural Network

ANN's are developed based on the way biological nervous system and the brain works. They represent an adaptive information processing systems which consists of highly interconnected processing elements working

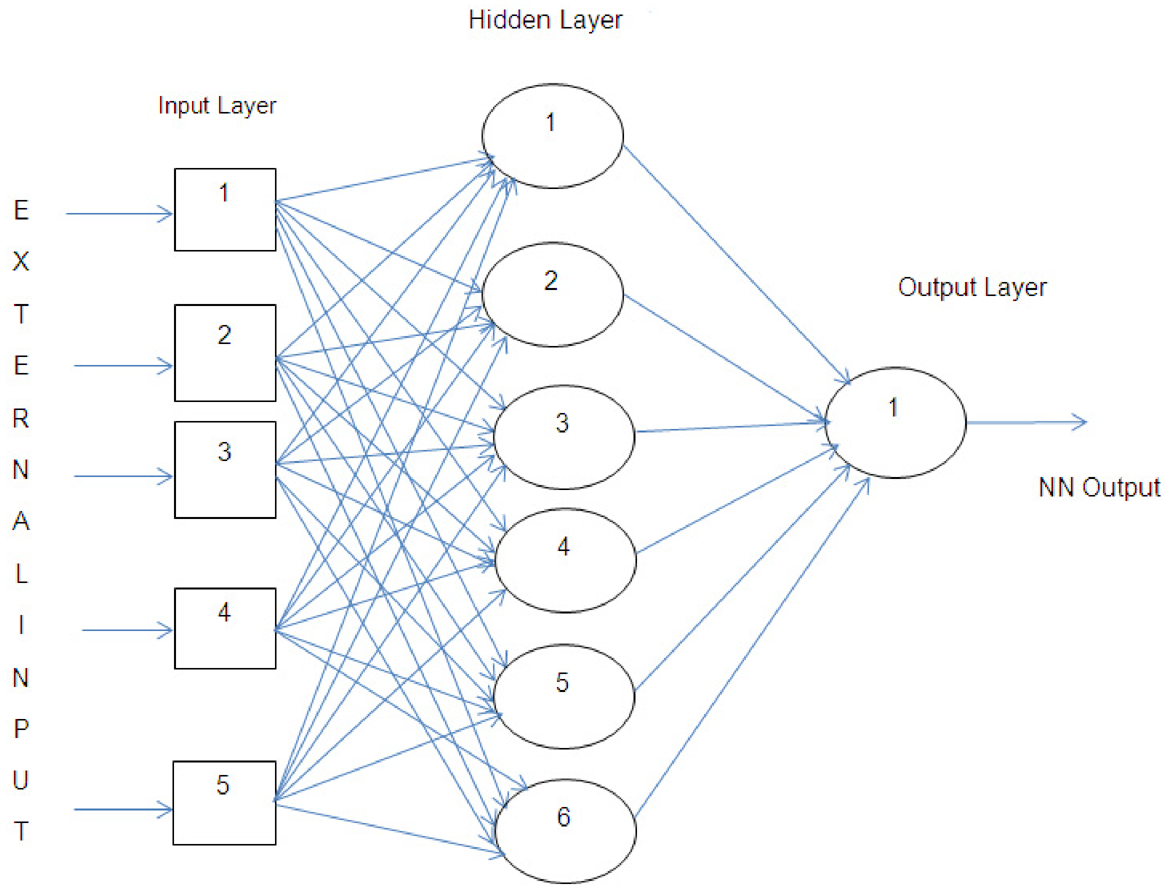

Fig. 2. Network architecture

together to solve problems. Neural Networks can be constructed as single-layered or multi-layered networks. In a single layered network, there is an input layer and an output layer along with weighted edges. The weights are summed; depending on the activation function an output from the network is generated using a non linear transfer function. The transfer function can be sigmoidal function or a threshold function, in the case of sigmoidal function the input changes gradually where for the later case the input is processed only when a certain threshold is reached, then switches off again [13–15]. Multi layered neural network on the other hand consists of an input layer, a hidden layer and an output layer. IMADA uses a multi-layered feed-forward neural network that utilizes the back-propagation algorithm. The network was prefered as it is effective, widely used and also can be easily adopted to suit our needs.

The neural network architecture consists of a five input layer agent with one hidden layer and with six hidden neurons and one output layer shown in Figure 2.

The weights are randomized in the beginning and the transfer function used is sigmoidal as given in Equation 1, where Y is the output, x the input and e the exponential function.

$$Y = \frac{1}{1 - e^{-x}} \tag{1}$$

Let Y be the expected output from the network and X is the input, W the randomly assigned weight and g the transfer function, the output is represented as in Equation 2,

$$Y = g(\sum W.X) \tag{2}$$

Again, let E be the error function and the root mean square error as defined as in Equation 3:

$$E = \frac{1}{2}{E_{rr}}^2 \tag{3}$$

The weights are updated using the updating rule given by Equation 4 until the error is minimized and desired output reached.

$$W_j \leftarrow W_j + \alpha E_{rr} \times g'(in)X_j \tag{4}$$

Here α, denote the learning rate. The weights are updated and set so that the average squared error or energy is at it lowest, tending to reach the global minima. If the actual output generated by the network matches the desired or target output then the network has completed its learning. The learning rate is kept constant during the training process of the network. The output from the network are crisp for instance $1, 2, 3, 4, 5$. For human to interpret this output a fuzzy logic component has been used.

4. Fuzzy Logic

The fuzzy set 'A' is defined by [16] as a set of ordered pairs, where, $\mu_A(.)$ is called the membership function of A and $\mu_A(x)$ is the grade or degree of membership of x in 'A', which indicates the degree that x belongs to the fuzzy set 'A', as shown in Equation 5:

$$A = (x, \mu_A(x))|x\varepsilon A, \mu_A \varepsilon[0, 1] \tag{5}$$

where, each element x in 'A' is a real number A(x) in the interval [0, 1] which is assigned to x. Larger values of $\mu_A(x)$ indicate higher degrees of membership [16]. Using a fuzzy logic agent, the crisp values are transformed with grade boundaries of memberships representing linguistic terms. The fuzzy logic agent maps the crisp output from the neural network via the membership function into different non-crisp grades. An example of the output membership function for the level of depression is shown in Figure 3.

The output action in words is defined as:

1. Very high,
2. High,
3. Medium,
4. Low, and
5. Very low.

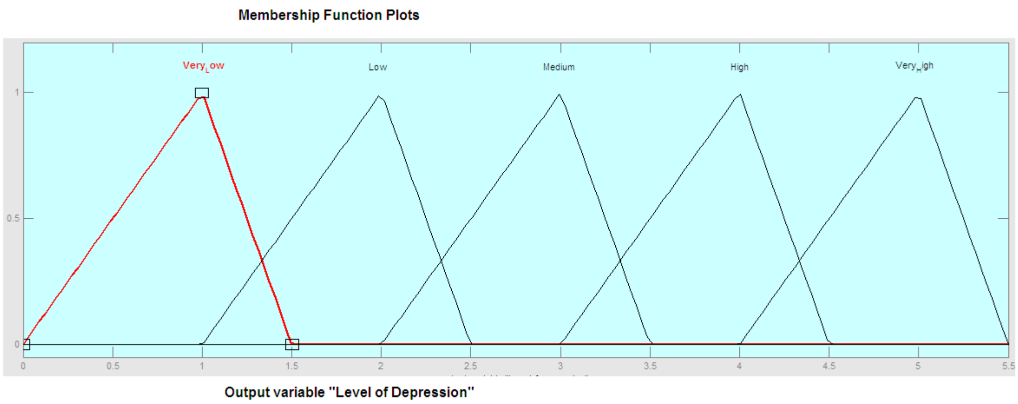

Fig. 3. Output membership function for the level of drepression

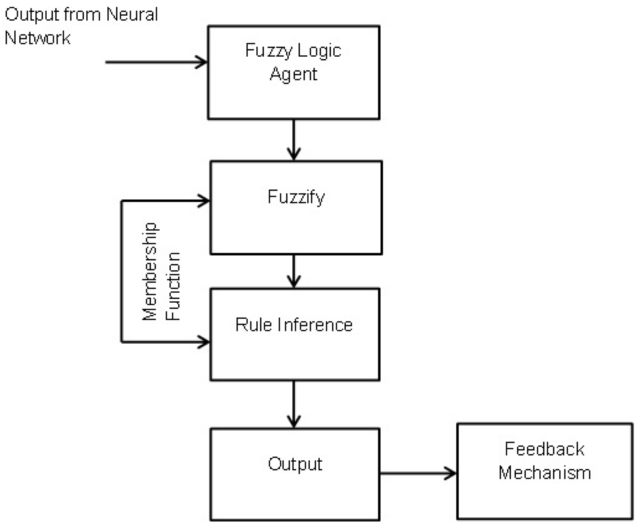

Fig. 4. Work-flow diagram for the fuzzy logic agent

A work-flow diagram for the fuzzy logic agent is given in Figure 4.

A sample of the rule-base is shown as Listing 1.

Listing 1. *getFuzzyClassification* Function

```
function getFuzzyClassification($user,$avg)
{
  if (($user>5)&&($avg<5))
    return ‘‘ very high”;
  else if (($user<4)&&($avg<5))
    return ‘‘high”;
  else if (($user>3)&&($avg<3))
    return ‘‘low”;
  else if (($user>2)&&($avg<2))
    return ‘‘very low”;
  else
    return ‘‘medium”;
```

5. Results and Outcome from the Modified Model

The model was integrated and then tested with work-stress data. The present study uses data that has been collected from four Australian States which are New South Wales (NSW), Western Australia (WA), South Australia (SA) and Tasmania (TAS). Data was also collected from two Australian Territories namelyAustralian Capital Teritorry (ACT) and Northern Territory (NT) [17, 18]. The survey questionnaire was developed based on the Australian Workplace Barometer (AWB). The main issues based on which the questionnaire was developed are:

1. Demand and pressure,
2. Resource, support and control,
3. Job satisfaction and engagement,
4. Bullying and violence,
5. Work-family balance,
6. Physical health and psychological wellbeing,
7. Burnout and cardiovascular risk.

Table 1. Sample Australian Workplace Barometer Questionnaire

Mental Health-Depression	Read Option, Single Response	Option1: Not at all	Option2: Several Days	Option3: More than half a day	Option4: Nearly everyday	Option5: Refused
Q1: During the Last month, how often were you bothered by little interest or pleasure in doing things.						
Q2: During the last month, how often were you bothered by feeling down, depressed or hopeless?						
Q3: During the Last month, how often were you bothered by trouble falling or staying asleep OR sleeping too much?						
Q4 During the Last month, how often were you bothered by feeling tired or having little energy?						
Q5: During the Last month, how often were you bothered by poor appetite or overeating						
Q6: During the Last month, how often were you bothered by feeling bad about yourself or that you are a failure or have let yourself or your family down?						
Q7: During the Last month, how often were you bothered by trouble concentrating on things, such as reading a newspaper or watching television.						
Q8: During the Last month, how often were you bothered by moving or speaking so slowly that other people could have noticed OR- the opposite-being so fidgety or restless that you have been moving around a lot more than usual?						
Q9: During the Last month, how often were you bothered by thoughts that you would be bette off dead or thoughts of hurting yourself in some way?						

Using the present model the data from all of the above category has been tested [2]. The modified model will only use data collected on issues based on psychological wellbeing. The questions tailored for this section of the questionnaire is given in Table 1, consisting of nine questions based on the psychological wellbeing (Mental health -depression) for this study [17, 18].

The data collected using the questionnaire are normalized, missing values replaced by mean for that particular column and then analyzed. The neural network takes five parameter input: *Industry, User Mean, Total Mean, Mean+2SD, Mean-1SD*, which are chosen as the user level of work stress will be benchmarked based on the industry they work. The user mean for a particular section of the questionnaire (depression in this case) is calculated. The Total mean is the mean calculated for the same section of the questionnaire data collected nationally. The standard deviation (SD) for the user mean for depression is calculated then the mean plus minus the standard

Table 2. Input and Desired Output from the Neural Network

		INPUTS			OUTPUT
Q8B	Mean Total	Mean+2SD	Mean-1SD	Depression per user	Output
4	2.7368	9.6134	-0.7014	13.6060	5
10	3.8433	11.8533	-0.1616	4	4
13	3.6797	0.0412	-0.0509	6	5
10	3.8433	11.8533	-0.1616	1	2

Table 3. Output from the Neural Network

		INPUTS	OUTPUTS	
Q8B	Mean Total	Depression per user	Target Output	Network Output
4	2.7368	13.6060	5	4.4505
10	3.8433	4	4	4
13	3.6797	6	5	5
10	3.8433	1	2	2

Table 4. Desired Output from the Neural Network And Fuzzy Logic

		INPUTS		OUTPUTS	
Q8B	Mean Total	Depression per user	Target Output	Network Output	Fuzzy Output
4	2.7368	13.6060	5	4.4505	High
10	3.8433	4	4	4	High
13	3.6797	6	5	5	High
10	3.8433	1	2	2	Low

deviation is calculated [2]. The Table 2 depicts the input to the neural network and the desired output from the network. The six parameter in the table represent:

1. Industry (Q8B): different industry,
2. Total Mean: is the mean for each row of responses collected via the AWB questionnaire for each section,
3. Mean + 2SD: is the mean plus two Standard Deviation,
4. Mean - 1SD: is the the mean minus one Standard Deviation,
5. Depression per user: is the response from the user completing the questionnaire,
6. Output: desired output from the neural network.

Table 3 shows the output generated from the neural network, the output matches the target output.

Using fuzzy logic the crisp values from the neural network as shown in Table 2 is transformed into grades of membership function for linguistic term of its fuzzy set are shown in Table 4. and the surface graph showing the level of depression using average mean for benchmarking and the depression per user as in Figure 5.

On completing and submitting the survey, each individual user receives feedback that is benchmarked with the accumulated data from people working in the same industry, at different cities in real time. Using this feedback they can compare where they stand as regards to their working conditions and work-related stress. This information will also enable them to make informed decision and possible changes to their contribution or working condition.

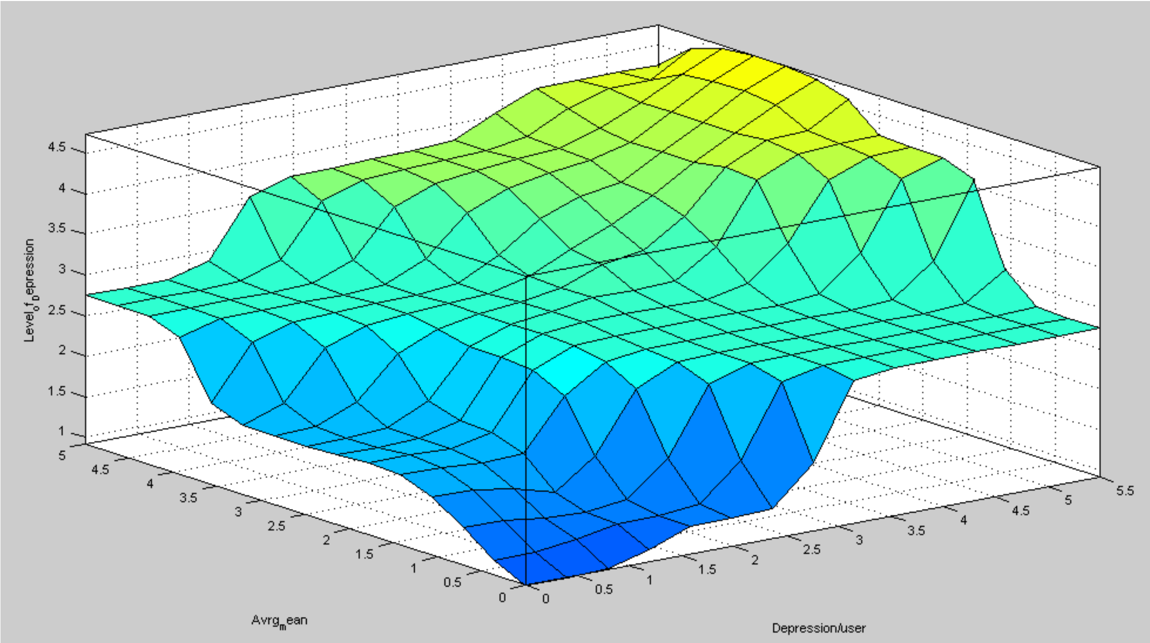

Fig. 5. Surface graph showing the level of depression, average mean for benchmarking and the depression per user

6. Conclusion and Future

This paper presents a hybridized multi-agent oriented approach to develop a model which classify and linguistically grades the level of stress from accumulated work-related stress data. It uses a neural network agent to classify the data and then a fuzzy logic agent to gradually transform the crisp output from the neural work into linguistic outputs. In this case the results reproduced those derived by human Subject Matter Expert (SME)'s. The main idea of integrating neural network and fuzzy logic techniques was to neutralize each other's weaknesses and generate a superior hybrid solution. The result demonstrated that using this technique, the work-stress data was classified efficiently and the measured stress level was successfully described in linguistic term (Human readable). This achievement provides the user with an automated mechanism. The mechnism can render a first step towards identification, prevention, and making perceptible changes to the working environment. The IMADA uses a hybridized technique that provided better solution in terms of applicability, portability and efficiency in this particular psychological domain. Future work can include an emotion recognizer agent that will records/capture emotions of the user that undertakes the work-stress related survey, adding another dimension, enabling more in-depth analysis of work-stress related data.

7. Acknowledgment

The research work is supported by the Australian Research Council Linkage Grant LP 100100449.

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